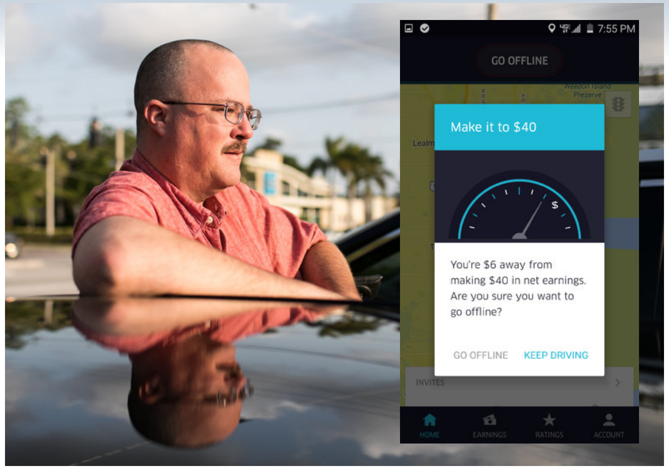
Ethics of
Artificial Intelligence

Ethics of AI

Will a new technology:

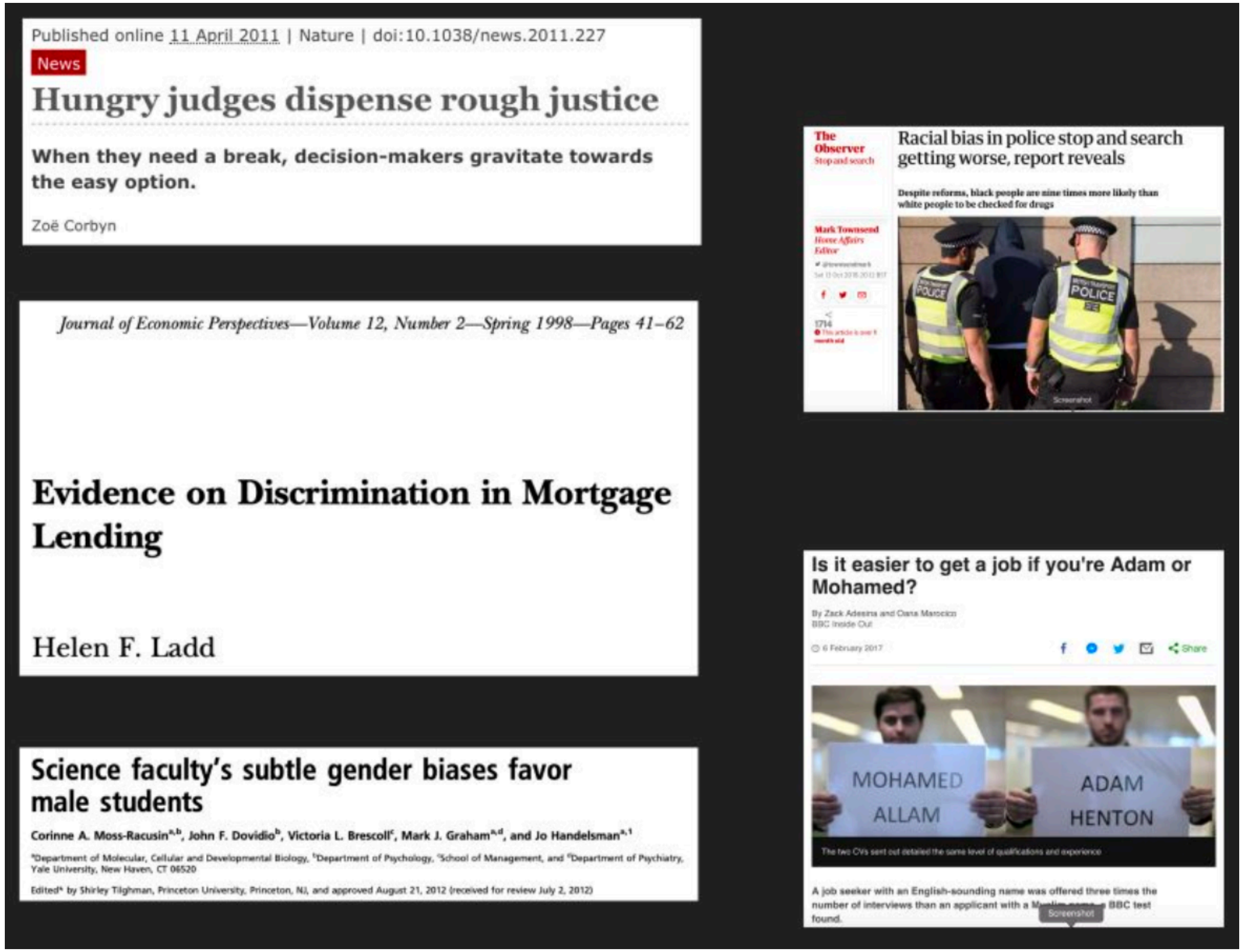
- disempower **individuals vs corporations**?
  - ⇒ user modeling; data mining; fostering addictive behaviors; developmental effects on children
- disempower **individuals vs governments**?
  - ⇒ facilitate disinformation (deep fakes; bots masquerading as people; filter bubbles); enable qualitatively new military or security tactics
- take **autonomous actions** in a way that obscures responsibility
  - ⇒ autonomous weapons; self-driving cars; loan approval systems
- disproportionately affect **vulnerable/marginalized groups**
  - ⇒ automated decision making tools trained in ways that may encode existing biases



BIAS AND FAIRNESS

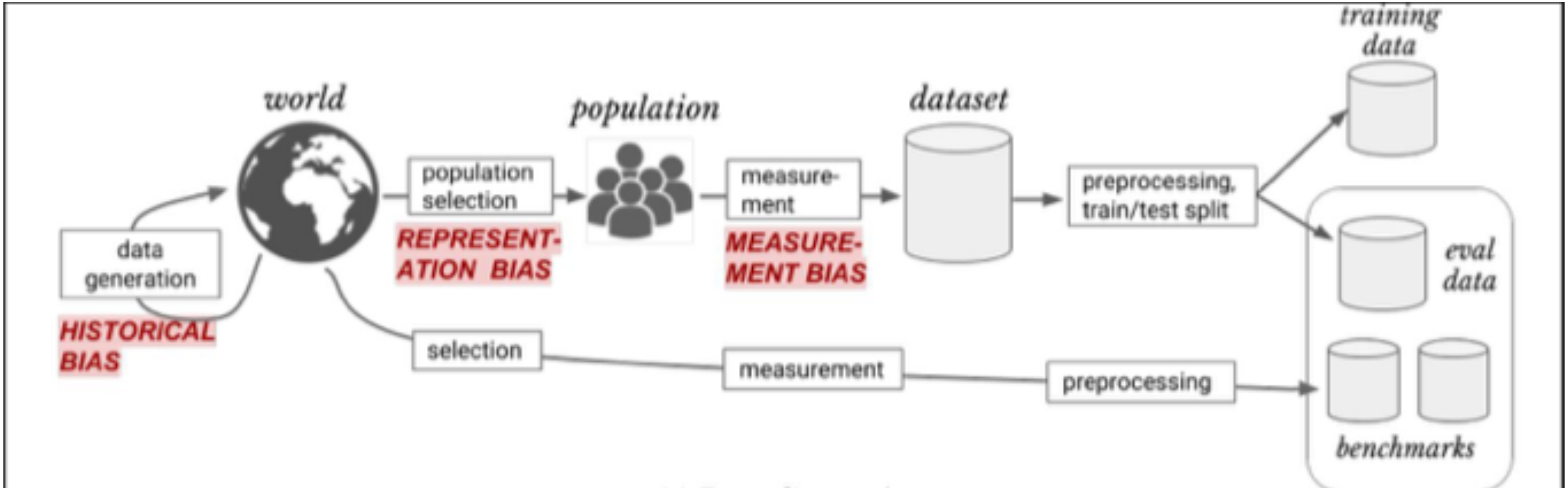
Human bias

Bias in people refers to our tendency to take quick decisions based on little information



Can technology have bias?

Sources of bias in ML algorithms



(a) Data Generation

Historical bias

Historical bias arises when there is a misalignment between world as it is and the values or objectives to be encoded and propagated in a model. It is a normative concern with the state of the world, and exists even given perfect sampling and feature selection.

Example: image search In 2018, 5% of Fortune 500 CEOs were women (Zarya, 2018). Should image search results for "CEO" reflect that number? Ultimately, a variety of stakeholders, including affected members of society, should evaluate the particular harms that this result could cause and make a judgment. This decision may be at odds with the available data even if that data is a perfect reflection of the world. Indeed, Google has recently changed their Image Search results for "CEO" to display a higher proportion of women.

Representation bias

Representation bias arises while defining and sampling a development population. It occurs when the development population under-represents, and subsequently fails to generalize well, for some part of the use population. [1]

1. **The sampling methods only reach a portion of the population.** For example, datasets collected through smartphone apps can under-represent lower-income or older groups, who are less likely to own smartphones. Similarly, medical data for a particular condition may be available only for the population of patients who were considered serious enough to bring in for further screening.

2. **The population of interest has changed or is distinct from the population used during model training.** Data that is representative of Boston, for example, may not be representative if used to analyze the population of Indianapolis. Similarly, data representative of Boston 30 years ago will likely not reflect today's population.

Measurement bias

Measurement Bias arises when choosing and measuring features and labels to use; these are often proxies for the desired quantities. The chosen set of features and labels may leave out important factors or introduce group- or input-dependent noise that leads to differential performance.

1. **The measurement process varies across groups.** For example, if a group of factory workers is more stringently or frequently monitored, more errors will be observed in that group. This can also lead to a feedback loop wherein the group is subject to further monitoring because of the apparent higher rate of mistakes (Barocas and Selbst, 2016;

2. **The quality of data varies across groups.** Structural discrimination can lead to systematically higher error rates in a certain group. For example, women are more likely to be misdiagnosed or not diagnosed for conditions where self-reported pain is a symptom (Calderone, 1990). In this case, "*diagnosed* with condition X" is a biased proxy for "has condition X."

3. **The defined classification task is an oversimplification.** In order to build a supervised ML model, some label to predict must be chosen. Reducing a decision to a single attribute can create a biased proxy label because it only captures a particular aspect of what we really want to measure. Consider the prediction problem of deciding whether a student will be successful (e.g., in a college admissions context). Fully capturing the outcome of 'successful student' in terms of a single measurable attribute is impossible because of its complexity. In cases such as these, algorithm designers resort to some available label such as 'GPA' (Kleinberg et al., 2018), which ignores different indicators of success achieved by parts of the population.

Why worrying about bias in algorithms

Decisions made by a ML algorithm are:

- Cheap
- Scalable
- Automated
- Self-reinforcing
- Seemingly objective
- Often lacking appeals processes
- Not just predicting but also causing the future

Fairness in algorithms

- Nowadays, more attention is placed on algorithms being **fair**, and not just accurate.
- Fairness can be measured as:
  - demographic (or statistical) parity: population percentage should be reflected in the output classes
  - Equality of false negatives or equalized odds: constant false-negative (or both false-negative and true-negative) rates across groups.
  - Equal opportunity: equal True Positive Rate for all groups
  - Other metrics...
- Accuracy and fairness tend to be at odds with each other.
- Algorithms can be audited to test their fairness.
- *Are we ethically required to sacrifice accuracy for fairness?*

When the metric becomes the target (Goodhart's Law)

"When a measure becomes a target it ceases to be a good measure"

- Metrics introduced in the British public healthcare system (e.g. waiting time in ER) caused people to game it:
  - Cancelled scheduled operations to draft extra staff to ER
  - Required patients to wait outside the ER, e.g. in ambulances
  - Put stretchers in hallways and classified them as "beds"
  - Hospital and patients reported different wait times
- Big Data is significantly changing college applications (not in a good way)
  - Universities are given higher ranking for things such as receiving more applications, being more selective, and having more students accept their offers (while tuition is not considered)
  - This even pushed some mid-tier universities to reduce the number of offer letter sent out, especially to good students who they think would not accept. Students are losing their safety options
- Is this always undesirable? Can you think of ways to avoid this trap?

Algorithms to promote engagement

- Large, popular social media platforms use algorithms to increase user engagement
- Proposed content is designed to keep the user on the website longer
  - It also often becomes more extreme as the user follows the suggestions
  - Sometimes with very disturbing results: https://www.npr.org/sections/thetwo-way/2017/11/27/566769570/youtube-faces-increased-criticism-that-its-unsafe-for-kids
- They also tend to promote content that the user will agree/engage with, creating echo-chambers
  - Some theorize that echo-chambers can push people towards more extreme opinions
  - Do you agree? Should social media be required to change their recommendation algorithms to avoid these issues?
  - https://www.pnas.org/doi/10.1073/pnas.2023301118

Transparency and privacy trade-off

- There is a call for increased transparency in algorithms
  - What does that mean? Why does it matter?
- Transparency can sometime come at the cost of privacy and increased risks of data breaches or cyberattacks

Ethics of pricing algorithms

- Algorithms are currently used to adjust prices based on:
  - Willingness of buyer
  - Availability
- Uber surge pricing:
  - In 2014, terrorists attacked a café in Sidney, holding 10 customers and 8 employees hostage for 16 hours
  - During this time, people from the surrounding areas were evacuated. Transportation was disrupted.
  - Uber prices adapted by increasing the rate to a minimum of 100$
  - In general, underserved (poorer) areas get worse rates under current pricing policy
  - Does Uber have an ethical obligation to correct its pricing algorithms to protect vulnerable segments of the population?

Interesting reads